CiteSeer Find: k means parallel processing Documents Citations

Searching for **PHRASE k means parallel processing**.
Restrict to: Header Title Order by: Citations Hubs Usage Date Try: Amazon B&N Google (RI) Google (Web) CSB DBLP
Order: citations weighted by year.

Efficient gesture recognition algorithm based on Continuous.. - Susumu Seki (1995) (Correct)
thirteen times faster in the case using **k-means. Parallel Processing** For CDP matching, we calculate the
jisp.cs.nyu.edu/RWC/rwcp/people/yk/rwcp-doc/papers/1995/F-23_047.ps.gz

Try your query at: Amazon Barnes & Noble Google (RI) Google (Web) CSB DBLP

Efficient gesture recognition algorithm based on Continuous Dynamic Programming

Susumu SEKI Hiroshi KOJIMA Shigeki NAGAYA Ryuichi OKA
Information Integral Laboratory Theory and Novel Functions Department, RWCP
seki@trc.rwcp.or.jp

Introduction

It would be helpful, in situations in which humans and robots work in cooperation with one another, for the robots to be able to understand the humans' motions and help appropriately. To make this possible, it is important to perceive human motion in video images as sequences of individual movements. A number of techniques have been proposed for the recognition of human movements [1][2], and we ourselves have presented a gesture-recognition method focusing on real-time applicability[3]. Features of our model are:

- Use temporal edges as a feature
- To use Continuous Dynamic Programming (CDP) for matching against the models [4]

The temporal edges are obtained by passing the input from a CCD camera through temporal-differencing, spatial-reduction, temporal-averaging, and logarithmic processing, producing what we call a "feature-image". All of these processes are comparatively simple, and are thus well suited to real-time recognition systems. CDP matching is one a group of methods known as "spotting" techniques, and is capable of producing a result for each frame as it is processed. Also, because the amount of matching time it is requires is only proportional to the total number of frames in a model, it is commonly used in the field of voice recognition. For image recognition, however, for every unit of time, the number of dimensional distances that have to be calculated for feature-images is equal to the total number of frames —and this poses a problem when constructing systems capable of recognizing large-scale models.

- clustering using the k-means method, and
- reducing computation-time by parallel processing.

Clustering

The diverse gestures made by human beings can be thought up of as being constructed from a set of simple elemental movements. It can be effective, particularly for systems using large-scale models, to classify these movements into categories, and then to express gestures using category numbers. Also, if the number of categories is smaller than the total number of models, this can be a useful technique for improving speed, since the number of times distance between feature-images into categories, and then conducted recognition tests.

Table 1: Recognition-ratios Using Clustering (%)

Feature-image	98
32Clusters	83
64Clusters	95

Recognition Testing

The gestures that served as the objects of recognition consisted of four types of motions:(1)putting down a book, (2)opening the book, (3)turning to the next page, (4)returning to the previous page, (5)closing the book, and (6)holding the book. These were filmed from seven different directions fifteen degrees apart, centered on the position directly in front of the experimental subject, for a total of 42 models. We then checked the recognition-ratio using the same human subject, wearing the same clothes, against the same background, for all 6 motions × 7directions (Table 1). Our input-image size was 256×256, the feature-image size was 16×16, and the temporal-averaging constant was three frames. This test showed that, assuming that one selects an appropriate number of clusters, there is hardly any difference from the case in which the distance calculations are made using the feature-image directly.

Calculating Time

Next, we conducted comparisons of calculating time between the case in which the feature-images were used and that in which 64 clusters were used(Table2). The input video was 495 frames long, and the total number of frames in the standard-patterns was 967.
We found that the time required for distance calculations was thirteen times faster in the case using k-means.

Parallel Processing

For CDP matching, we calculate the local dis-

Your search matched **8** of **922177** documents.

A maximum of **8** results are displayed, **25** to a page, sorted by **Relevance** in **descending** order.
You may refine your search by editing the current search expression or entering a new one the text box.
Then click **Search Again**.

(parallel <near> clustering) and simultaneous

Search Again

Results:
Journal or Magazine = **JNL** Conference = **CNF** Standard = **STD**

1 **An Optical Bus Computer Cluster with a deferred cache coherence protocol**
Shibayama, S.; Hamaguchi, K.; Fukui, T.; Sudo, Y.; Shimoyama, T.; Nakamura, S.;
Parallel and Distributed Systems, 1996. Proceedings., 1996 International Conference on , 3-6 Jun 1996
Page(s): 175 -182

[Abstract] [PDF Full-Text (784 KB)] **IEEE CNF**

2 **SWEB: towards a scalable World Wide Web server on multicomputers**
Andresen, D.; Tao Yang; Holmedahl, V.; Ibarra, O.H.;
Parallel Processing Symposium, 1996., Proceedings of IPPS '96, The 10th International , 15-19 Apr 1996
Page(s): 850 -856

[Abstract] [PDF Full-Text (716 KB)] **IEEE CNF**

3 **A clustered approach to multithreaded processors**
Krishnan, V.; Torrellas, J.;
Parallel Processing Symposium, 1998. 1998 IPPS/SPDP. Proceedings of the First Merged International...and Symposium on Parallel and Distributed Processing 1998 , 30 Mar-3 Apr 1998
Page(s): 627 -634

[Abstract] [PDF Full-Text (796 KB)] **IEEE CNF**

Table 2: Calculation Time (s)

	Feature	64Clusters
Local-distance Calculation	56.2	0.2
Categorization	0.0	4.2
Total	56.2	4.4

tance $d(t,\tau)$ between input frame t and standard-pattern frame τ, for all of the standard-patterns. Then, using these results, we progressively calculate the cumulative distance $S(t,\tau)$ for each pattern, as follows:

$$S(-1,\tau) = S(0,\tau) = \infty \quad (1 \leq \tau \leq T) \tag{1}$$

$$S(t,1) = 3 \cdot d(t,1) \tag{2}$$

$$S(t,2) = \min \begin{cases} S(t-2,1) + 2 \cdot d(t-1,2) + d(t,2) \\ S(t-1,1) + 3 \cdot d(t,2) \\ S(t,1) + 3 \cdot d(t,2) \end{cases} \tag{3}$$

$$S(t,\tau) = \min \begin{cases} S(t-2,\tau-1) + 2 \cdot d(t-1,\tau) + d(t,\tau) \\ S(t-1,\tau-1) + 3 \cdot d(t,\tau) \\ S(t-1,\tau-2) + 3 \cdot d(t,\tau-1) + 3 \cdot d(t,\tau) \end{cases} \quad (3 \leq \tau \leq T) \tag{4}$$

The cumulative distance S can be calculated in parallel for each frame of each standard-pattern. Accordingly, we converted the algorithms for parallel processing and ran calculating-time tests, using a CRAY CS6400 as our computer. At present, the CS6400 at RWCP has 12 CPU's. Since one of these, however, is used ad the system controller, we ran our comparison on the remaining 11 CPUs. The result showed a calculation speed 4.2 times faster than on a 1-CPU system.

The Real-time Gesture-spotting System

Based on the results of the experiments we have conducted up to now, we have created a system that recognizes gestures in real-time(30 times per second). The series of images coming from the CCD camera is passed as input into an off-the-shelf general-purpose image-processing board(IMAGING TECHNOLOGY Series 150/40). This board runs edge-extractions, spatial reduction, and temporal averaging on the images. All of the feature-extraction parameters are the same as the values we used in the test system. The memory on

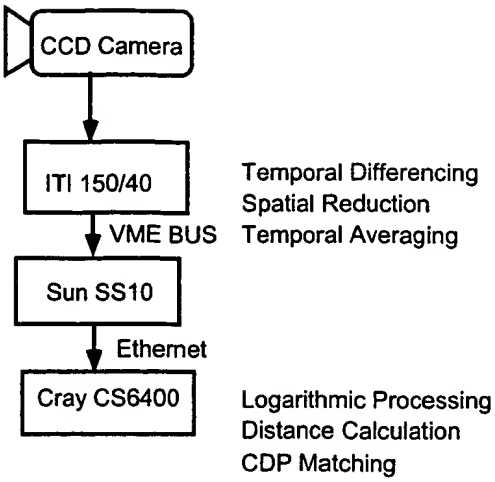

Figure 1: System Configuration

the image-processing board can be accessed from the host workstation, a Sun SS10. The feature-images produced in that on-board memory are than transferred via socket-communication to the CS6400, which conducts the CDP and the logarithmic processing (Fig.1). We have verified that our system can work in real time with 42 standard-patterns(containing 967 frames).

Conclusion

We have constructed a system with which it is possible to perform matching with a large number of models in real time. In the future, we plan to develop more efficient ways of representing gestures, to construct a noise-robust system, and to raise the efficiency way of our parallel processing.

References

[1] Yamato J., Ohta J. and Ishii K,:"Recognizing Human Action in Time-Sequential Images Using Hidden Markov Models", Trans. of IEICE(D-II),**J76-D-II**, 12, pp.2556-2563(1993-12)(in Japanese).

[2] Darrell T. and Pentland A.!' "Space-Time Gestures", Proc. IJCAI'93 Looking at People Workshop(Aug. 1993).

[3] Takahashi K., Seki S., Kojima K. and Oka R. : "Spotting Recognition of Human Gestures from Time-Varying Images ", Trans. of IEICE(D-II)!" **J77-DII**,8, pp.1552-1561(1994-08).

[4] R.Oka:"Continuous Words Recognition with Continuous DP", Report of the Acoustic Society of Japan,**S78-20**, pp.145-152(1978-06)(in Japanese).

Your search matched **1** of **922177** documents.

A maximum of **1** results are displayed, **25** to a page, sorted by **Relevance** in **descending** order.
You may refine your search by editing the current search expression or entering a new one the text box.

Then click **Search Again.**

simultaneous <near> move and cluster

Search Again

Results:
Journal or Magazine = **JNL** Conference = **CNF** Standard = **STD**

1 **Physical planning with retiming**
Cong, J.; Sung Kyu Lim;
Computer Aided Design, 2000. ICCAD-2000. IEEE/ACM International Conference on , 2000
Page(s): 2 -7

[Abstract] [PDF Full-Text (624 KB)] **IEEE CNF**

4 **Parallel programming in multi-paradigm clusters**
Leichtl, J.; Crandall, P.E.; Clement, M.J.;
High Performance Distributed Computing, 1997. Proceedings. The Sixth IEEE International Symposium on , 5-8 Aug 1997
Page(s): 326 -335

[Abstract] [PDF Full-Text (892 KB)] **IEEE CNF**

---

5 **PC clusters for signal processing: an early prototype**
Chapin, J.; Chiu, A.; Hu, R.;
Sensor Array and Multichannel Signal Processing Workshop. 2000. Proceedings of the 2000 IEEE , 2000
Page(s): 525 -529

[Abstract] [PDF Full-Text (376 KB)] **IEEE CNF**

---

6 **WWW-based high performance computing support of acoustic matched field processing**
Gever, D.H.; Fabozzi, D.J., II;
OCEANS, 2001. MTS/IEEE Conference and Exhibition , Volume: 4 , 2001
Page(s): 2541 -2548 vol.4

[Abstract] [PDF Full-Text (1310 KB)] **IEEE CNF**

---

7 **Hybrid evolutionary search method based on clusters**
Ming Li; Hon-Yuen Tam;
Pattern Analysis and Machine Intelligence, IEEE Transactions on , Volume: 23 Issue: 8 , Aug 2001
Page(s): 786 -799

[Abstract] [PDF Full-Text (1192 KB)] **IEEE JNL**

---

8 **A new method for transparent fault tolerance of distributed programs on a network of workstations using alternative schedules**
Das, D.; Dasgupta, P.; Das, P.P.;
Algorithms and Architectures for Parallel Processing, 1997. ICAPP 97. 1997 3rd International Conference on , 10-12 Dec 1997
Page(s): 479 -486

[Abstract] [PDF Full-Text (824 KB)] **IEEE CNF**

L Number	Hits	Search Text	DB	Time stamp
-	3692	(change with membership) update with (cluster center)	USPAT; US-PGPUB; EPO; JPO; DERWENT; IBM_TDB	2003/02/26 07:26
-	34	(change with membership) and update with (cluster center)	USPAT; US-PGPUB; EPO; JPO; DERWENT; IBM_TDB	2003/02/26 07:34
-	448	move with subset	USPAT; US-PGPUB; EPO; JPO; DERWENT; IBM_TDB	2003/02/26 07:34
-	57	(move with subset) and cluster	USPAT; US-PGPUB; EPO; JPO; DERWENT; IBM_TDB	2003/02/26 07:39
-	474	move with (data adj points)	USPAT; US-PGPUB; EPO; JPO; DERWENT; IBM_TDB	2003/02/26 09:05
-	2518	parallel with cluster$4	USPAT; US-PGPUB; EPO; JPO; DERWENT; IBM_TDB	2003/02/26 09:37
-	963	(parallel with cluster$4) and move	USPAT; US-PGPUB; EPO; JPO; DERWENT; IBM_TDB	2003/02/26 09:06
-	543	((parallel with cluster$4) and move) and center	USPAT; US-PGPUB; EPO; JPO; DERWENT; IBM_TDB	2003/02/26 09:06
-	255	(parallel with cluster$4) and cluster with center	USPAT; US-PGPUB; EPO; JPO; DERWENT; IBM_TDB	2003/02/26 09:37
-	100	(parallel near3 cluster$4) and ((parallel with cluster$4) and cluster with center)	USPAT; US-PGPUB; EPO; JPO; DERWENT; IBM_TDB	2003/02/26 09:37
-	24887	zhang.in.	USPAT; US-PGPUB; EPO; JPO; DERWENT; IBM_TDB	2003/02/26 09:50
-	304	zhang.in. and cluster	USPAT; US-PGPUB; EPO; JPO; DERWENT; IBM_TDB	2003/02/26 09:50
-	84	(zhang.in. and cluster) and move	USPAT; US-PGPUB; EPO; JPO; DERWENT; IBM_TDB	2003/02/26 09:53
-	108	(Hsu Kleyner).in. and cluster	USPAT; US-PGPUB; EPO; JPO; DERWENT; IBM_TDB	2003/02/26 14:04

-	2264	parallel$3 with cluster	USPAT; US-PGPUB; EPO; JPO; DERWENT; IBM_TDB	2003/02/26 21:30
-	45311	simultaneous$4 with move	USPAT; US-PGPUB; EPO; JPO; DERWENT; IBM_TDB	2003/02/26 21:29
-	43	(parallel$3 with cluster) and (simultaneous$4 with move)	USPAT; US-PGPUB; EPO; JPO; DERWENT; IBM_TDB	2003/02/26 21:29
-	1305	parallel$3 near5 cluster	USPAT; US-PGPUB; EPO; JPO; DERWENT; IBM_TDB	2003/02/26 21:30
-	53	(parallel$3 near5 cluster) and (data adj points)	USPAT; US-PGPUB; EPO; JPO; DERWENT; IBM_TDB	2003/02/26 21:56